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Coherence Analysis in the Brain Network of ASD Children using Connectivity Model and Graph Theory

Menaka R*, Karthik R, Aaditya Parthasarathy, Manideep P & Varsha V
Centre for Cyber Physical Systems, School of Electronics Engineering, Vellore Institute of Technology, Chennai 600 127, India

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Autism Spectrum Disorder (ASD) belongs with the category of neuro-developmental disorders, which can be majorly categorized under decreased social relationships, communication and thought processes. Various studies in the field of biological networks prove that one of the defining features of ASD is altered brain connectivity. Hence, the understanding of the brain networks can pave the way to delve deeper into the underlying behaviour of the Autistic brains. Moreover, many studies also reveal that human brains exhibit small-world characteristics which are usually seen in simple model neural networks that emerge spontaneously upon adaptive rewiring according to the dynamical functional connectivity. Graph theory-based approaches are finding their way into the understanding of the altered connectivity in various neurological disorders. For that matter, the study focuses on implementing a graph theory-based approach to investigate on the small-world network of Autistic as well as typically developing brains and understand the behavioural changes for an Audio and Video Stimuli. The graphically generated data is then measured for functional connectivity using a symmetrical parameter known as the coherence measure.

Keywords: Autism spectrum disorder, Biological network, Coherence measure, Functional connectivity

Introduction

Autism Spectral Disorder (ASD) is a class of neuro-developmental disorders that are mostly characterized by lesser than optimal levels of social communication and the subsistence of repetitive patterns of behaviour and activities.[1] ASD mainly materializes in the early days of life and has a gender bias of 4:1 tilting more towards the male gender.[2] It is usually perennial, and the impairments of their senses are quantifiably low. They might be extremely sensitive or under sensitive to all kinds of sensory stimulus.[2] It is now evident that there is a dearth of knowledge and statistics to have a holistic understanding of the subject. It is abstruse as to the manifestation of the symptoms of ASD and its changes from childhood to later adolescence.[3] Several symptoms of ASD include being irresponsive to their name by about 12 months of age, avoiding eye contact, having delayed speech and language skills, echolalia, tendency to be alone and also have obsessive interests and disinterest in feelings as a whole. In Bock *et al.* [4], the author stresses the point that early detection of ASD is very important as the prevalence rate of ASD has seen to increase in various places across the globe for the past decade.

The studies conducted on adults in Hollocks *et al.*[5] shows the prevalence of autism in adults, and ties in the correlation between ethnicity and their community. It is also observed that as age increases, the symptoms also increase. The various distinctive features of ASD vary widely and depend on the age, cognitive ability, and their ability to communicate properly and articulately. There seems to be a greater link between spoken language and ASD. When they can speak much better than before, then the number of symptoms they exhibit decreases.[6] Presently, the detection and identification of autism is done in many ways; checklist based and reading based. In India, the prevailing guidelines on this topic are addressed in Indian Scale for Assessment of Autism (IASM) and the Diagnostic Statistic Manual.[7] In some other countries, question-based studies are used to identify the disorder, mainly CHAT and M-CHAT.[8] CHAT is based on 14 questions that initially served as a checklist for autism in toddlers. This is however used for children who are lesser than two to three years. M-CHAT is a modified form of CHAT and this has about twenty-three questions that are yes/no based. This served as a better version of the former and was used predominantly used in the last decade. However, there were limitations in this study as well, as being questions they could not address the neuro-biological aspects of the disorder, and hence the

*Author for Correspondence
E-mail: menaka.r@vit.ac.in

researchers were invited to many false positives which hindered the study of its reach. Also, these are not representative of autism in older people as their needs and actions vary highly than that of the children. However, there have been many implications discussed in Havdahl *et al.*[9], which suggests that the method used in Rescorla *et al.*[10] is less successful for the children with developmental and emotional/behavioural problems. Bogdan *et al.*[11] explains a multimodal approach to understand an Autistic brain, by combining EEG, fMRI and DTI by studying their neurological basis.

In-order to delve into the intricacies of a complicated disorder like Autism, it is necessary to understand the processes that takes place within the neural system. To get a clearer picture of the pathological process, the Autistic brain activities are compared with that of the Normal processes in the brain. While either of them calls for a necessity to understand a complex network that connects several nodes and works in parallel. What makes it complex is the process of understanding the hidden dependencies that is observed in a dynamically performing system of networks that are capable of executing various tasks simultaneously in a given frame of time.[12] While picking a method to understand the brain connectivity, one must beware that the swift temporal progression of how the data has been integrated from diverse sections of the brain performs very important role in understanding such complex disabilities like that of Autism. For this purpose, the information provided by the imaging techniques like fMRI has proven to be insufficient and inaccurate, and hence EEG data has been incorporated largely for these kinds of studies, due to its good temporal resolution. Hence, this paper focuses on extracting the information from the EEG signals.

Electroencephalogram (EEG) is a non-invasive method for the assessment of electrical activity in the human brain. It involves recording of electrical signals of brain by attaching surface electrodes to the subject's scalp. It provides high temporal resolution i.e., sampling rates between 200 to 2000 Hz[13]. Koudelková *et al.*[14] from the literature reviews, it could be understood that EEG data plays a major role in analyzing Autism. Jolanta *et al.*[15] elucidates the EEG changes they are located in many different areas of the brain. It was reported that the anomalies in EEG are a neurophysiologic biomarker for the severity in cognitive and behavioural problems associated with ASD.[16] The paper also recommends EEG studies to be carried out in individuals who are diagnosed with ASD and would thereby help in identifying abnormalities. Another evidence throwing light to the importance of EEG was observed in Swatzyna *et al.*[17], which explains that most medications prescribed for ASD lower the seizure threshold and increase side-effects. Therefore, it may be prudent to order an EEG for ASD cases to validate the efficacy of the medicines and tests used.[18] Recently research is carried out to promote the use of EEG signals due to their effectiveness in giving ample amount of information necessary to understand the neural behaviour in depth and also, due to its economical nature.

Related Works

Autism is a kind of disorder, that although marks its onset at an early stage, will be detected in most of the cases, only once the behavioural changes become apparent. But these complex disorders however exhibit their functional signatures long before they can be identified through the behavioural symptoms.[19] The Human brain can be visualized as an organization of vast and complex network units that are interconnected by small units called neurons and are responsible to carry the information from the central processing unit of the brain. The functioning of a healthy brain depends on the effective communication between the various regions of the brain and within these regions, that are largely driven by the network of neurons.[20] The synchronization between the different regions of brain can be quantified to construct a functionally connected network. These complex networks show a self-similarity in all scales when characterized as dense locally connected networks and sparse long-range connected networks. These enable the networks to globally integrate all the information available, along with a local specialization. Bosl *et al.*[19] explains a comparative study made on the network properties using fMRI on the brains of adults as well as children, and their observation that it exhibited a scale-free organization or small-world organization with a difference in the hierarchical organization and inter-regional connectivity.

Many biological systems exhibit small-world connectivity. Due to which, the brain connectivity can be visualized and studied through the graph-theoretical approaches to examine the large-scale complex brain networks. Graphs are basically data structures having nodes and edges between them. In such a modelling representation, a node corresponds to a brain region and the edge corresponds to the functional connectivity between two regions.[21] And graph theory describes the mathematical representation of the relation between the nodes and edges. In the work of Smit *et al.*[22], the author explains in Fig. 1 about an article by Watts and Strogatz model, where the later authors describe a model of networks derived from biological or non-biological networks using – clustering coefficient C and average path length L. The former parameter represents the amount of local interconnectedness or the proportion of neighbouring vertices that are interconnected amongst each other, taking values between 0 and 1 while the later one represents the global inter-connectedness, or the average number of steps required to go from one vertex to another.

Though various methods are in the study for analyzing the EEG signals, like the statistical methods, linear analysis like coherence studies, the non-linear methods have been found to capture the dynamic brain activity. The studies on small-world networks have been trending in recent times with their applications in various health disorders. But, the study of autism disorders in Children and their early detection using EEG signals has found to be a novel area of research. Hence, we have focused largely on the application of Small-world networks to the EEG data to analyze and understand the behaviour of the human brain, especially the Autistic brains.

Small World Networks

A small-world network is defined quantitatively, as a combination of the high clustering and short path length between the nodes. As part of the rapid growth in the field of connectomes, the small world network began to be widely utilized as a metric and was applied for the analysis of various neuroimaging and

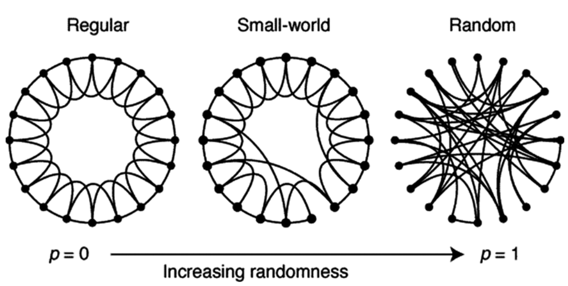

Fig. 1 — Watts and Strogatz model for Small-world network. Ring network represented in the top left corner has all its nodes connected to same number of nearest neighbours (l = 3), the second one is a Watts and Strogatz Model generated by removing each edge with a uniform and independent probability p, and rewiring them to get an edge between a pair of nodes chosen randomly. The last one represents a random network

other neuroscience data.[23] Hence, Small world networks are an important and feasible concept in the field of Neuroscience. It has been accepted however that small-worldness is a nearly universal and functionally valuable attribute of the nervous system, which are embedded economically in anatomical space. Network analysis of functional connectivity based on the graph theoretical models can provide information on the complex cognitive process happening within the brain and allow us to understand better, the relationship between the network structure and these processes.[24] The quantification of efficacious interactions between the various regions of the brain plays a vital role in the research of neuroscience. Many of the conventional methods rely on the simple linear methods to estimate the effective connectivity in the brain. However, usage of linear connectivity models oversimplifies the functions and dynamics of the brain. Thus, there is a need for non-causal relationships.[25] Studies on human connectomes suggests that, apart from the small-world features brain exhibit a modular small-world network along with rich club organization. Even with extremely simple models like coupled maps such properties can emerge sporadically from randomly organized networks with dynamic functional connectivity.[26] This however occurs in accordance to a principle that represents the structural plasticity in developing as well as adult brains, which is known as adaptive rewiring.

Moreover, there is enough evidence of an atypical functional connectivity in ASD, which suggests that the nature of such an atypical functionality in ASDs could vary over time with noticeable patterns of group differences across transient states. However, these transient relations between the networks of neurons cannot be captured using the conventional static functional connectivity analysis, hence dynamic functional connectivity approaches are incorporated. These studies could also find an overall predominance of static over connectivity and hyper variability over time in ASDs across numerous brain regions. The study in Dardo *et al.*[27] used fMRI data and analyzed the functional connectivity in ASD and NT subjects. They concluded that in contrast to the original hypothesis, their observation could reveal local-under connectivity in the anterior thalamus, and increased long range connectivity of thalamus with auditory, somatosensory, motoric and interoceptive cortices with parietal regions. Dynamic functional connectivity (dFC) is used to analyze the differences between individuals with Schizophrenia (SZ) and ASD.[28] The test shows that the dFC was able to distinguish the differences between SZ and healthy control, whereas, in the case of ASD, they weren't able to disparate the individuals using dFC and weren't as successful with ASD as they were in classifying SZ with temporal dynamic FC.

The small world connectivity analysis goes hand in hand with EEG signals for more effective and insightful analysis. The measures based on connectivity attained popularity particularly for the analysis of multiple electric signals recorded at the scalp using EEG. Iandolo *et al.* [29] uses small world networks and EEG readings to arrive at a novel method to study the resting state functional connectivity. The goal of the study is to extract graph-theory related metrics, such as small-worldness measures and use them as electrophysiological biomarkers. It gives useful perception about the possibility of incorporating hd-EEG and graph theory as robust tool to investigate the frequency-specific properties of the patterns of brain functional connectivity. The study in Stam *et al.*[30] investigated if the functional brain networks are atypically organized in Alzheimer 's disease (AD). Their results concluded that for a broad range of thresholds, the characteristic path length L was remarkably longer in the Alzheimer patients, whereas the cluster coefficient C showed no significant changes.

Graphical Methods

Recent studies on the brain have found to apply graph theory concepts to understand the functional connectivity of the neuronal network. These theories are suited well for the studies relating to disorders like ASD, since these are categorized under disconnection related syndromes, where functional disability is theoretically linked to the disruption or abnormal integration of spatially distributed regions of the brain, which normally constitute a large-scale network sub-serving function.[31] In the case of ASD the theory of developmental disconnection proposes a decreased long-range integration along with an increased local connectivity.[32]

A graph *G (V, E)* can be defined as a set of *n* vertices *V = {v1, v2, v3, ... vn}* and *m* edges *E = {e1, e2, e3, ... em}*, where an edge is a pair of vertices u and v which can be ordered *e = (u, v) € V×V* (directed graphs) or unordered *e = (u, v)* where *u, v € V*(non-directed graphs). In terms of the brain, the networks are described as a collection of nodes and edges, where the nodes indicate the electrode placement nodes and the edges indicate the associations between these nodes.[33] A valued graph or network comprises of the vertex set *V* and edge set *E* augmented with an edge value function *ρ* such that a real value *ρ (e)* is assigned to each of the edges.

Modelling the network is the primary step in the analysis. The network is modelled in the study using a Spiking Neural Network Architecture Model, known as NeuCube. During modelling phase, the interdependencies of the data input to the model is trained using the machine intelligence for all the subjects for each pair of the nodes. The result of training is obtained as an un-weighted undirected graph, which pictorially represents the strength of connections for each subject for each pair of nodes. The graph obtained after training is as shown in Fig. 2. After generating the graph, data characterization is done in-order to reduce the information by considering only the required network points and the connectivity strength involving those points for further analysis.

A connectivity measuring parameter is applied onto the weighted matrix obtained to measure the nodes that responds well for the stimuli and understand the nature of functional activities in Autistic brains. From the literature surveys made on the various parameters that can effectively analyze the connectivity measures, Coherence measures were found to give good results, especially with EEG data.[33] Coherence is a parameter that estimates the neural synchronization between two electrodes or nodes. The connections in the brain, that makes up the functional network are primarily measures of linear or non-linear

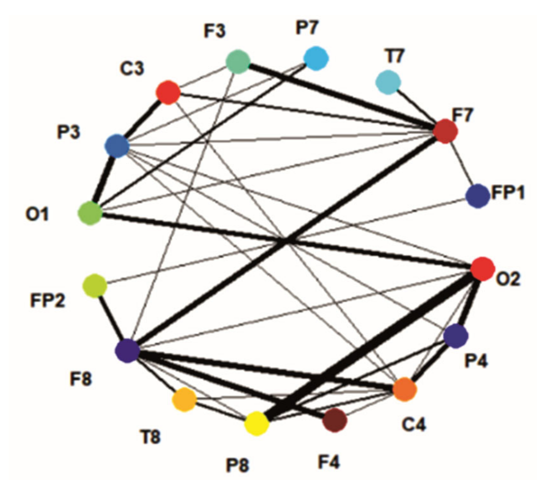

Fig. 2 — Graphical representation of the interactions between various nodes in the EEG data after training

statistical dependence of two time-series. Coherence exhibits itself as a measure of the stability in the phase correlations over time and is sensitive to both power and phase changes. The coherence between the distant brain regions have found to reflect the physiological activities at the sub-cortical neural networks, hence high values of coherence indicate a strong connectivity between those brain regions or co-occurrence of neuronal oscillations at same frequency while a low coherence value indicate the segregation of the nodes in the network.[33] Patterns of over and under connectivity can hence be measured by the coherence. Since specific brain sites have been mapped for certain cognitive function, this could easily help to understand the underlying nature of response towards the stimuli. A comparative analysis of both Normal and Autistic brains could help estimate the difference in the way of processing of the same stimuli for both the specimens under consideration. The coherence parameter in this study has been supported by Thomas *et al.*[34] which gives the functional analysis of different brain regions mapped with one another. As part of data characterization, only those channels mentioned in[35] were taken into consideration for the analysis.

Brain connectivity analysis are of three main categories a) Structural Connectivity, estimates the pattern of anatomical connections, typically the morphological change and plasticity, b) Functional Connectivity, measures the neuronal activation patterns of the structurally separated brain regions c) Effective Connectivity also details the influence of one neuronal system on another, thereby reflecting the interactions between active brain regions. Studies show that functional connectivity shows a positive correlation with structural connectivity and effective connectivity and, functional connectivity derive from the temporal characteristics of the brain. Functional connectivity has been explained as a statistical measure of temporal coherence or cross-correlation between two regions of the brain.[36–39] Hence coherence measures quantify the degree of association between two brain regions, hence evaluating the functional connectivity. Most of the studies that apply the coherence measures in brain connectivity analyses have been concentrating on ADHD or OCD.[33,39] The studies concentrating on ASD have been very less and mostly based on the study of Autistic Adults.[38] The utilization of coherence as a biomarker for early detection of Autism in growing children is a novel area of research and this has been the major motivation of this work.

In this study, we have considered the strength of the connectivity graph predicted by the spiking neural architecture (SNN) based NeuCube model to derive at the graphical representation of the data points acquired for the given stimuli. This graphical model is a Small-world network depicting the interactions of various regions of the brain is shown in Fig. 3. Unlike the works made in various literature reviews, we have tried to extract the path length manually depending on the thickness of the connections between various nodes. Since these are undirected graphs, the weights of the graphs could be converted to an $n \times n$ matrix, where n gives the number of electrodes from which the signal was acquired. The average of matrices for all the data samples could then be used for a comparative analysis. The average values for the samples from Normal and Autism data are then considered for the analysis of coherence. The coherence measures are applied here to analyze the connectivity graph and understand the nature of interaction between the pair of electrodes(nodes) to get a clearer view of the underlying behavioral pattern within the brain.

Research gaps and Significance of the proposed research

The proposed work effectively addresses the following research gaps in EEG signal analysis for Autism detection.

- The questionnaire-based diagnosis of autism results in false positive results and cannot address the neuro-biological aspects of the disorder.
- The studies about the hypo connectivity and hyper connectivity among the brain regions is in nascent stage.
- The study on the statistical dependencies between two regions of the brain can give better insight into the behaviour of the brain.
- The study on the physiological activities among the neural network regions must be developed for better understanding of the connectivity and interaction

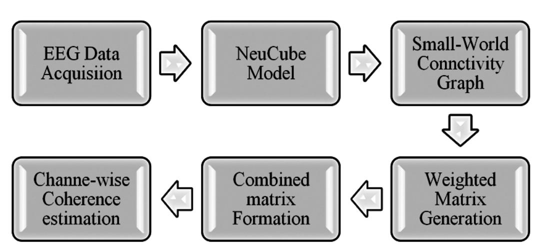

Fig. 3 — Workflow of the proposed work

among the regions, and the segregation of the nodes in the network.

Contributions

- The proposed work attempts for EEG analysis by utilizing the potential of graph theory, i.e., the small-world networks
- The small world connectedness among the brain regions is converted to weighted graph structure
- Creation of matrices for the graph for normal and autistic children
- Construction of the mean and standard deviation matrices based on the weight of the edges
- And a quantitative measure of coherence is done

Materials and Methods

The proposed workflow for the study is as depicted in Fig. 3. The approach consisted of two main parts, Data preparation and data processing. Machine learning was incorporated in the proposed system as part of data processing, to extract out the necessary information from the acquired data samples. Analyses were done on the processed data manually and the results were compared with the previous works studied from literature reviews.

Data Acquisition

EEG data were obtained from 9 subjects. Since the study is about early identification of autism in children, the subjects we have considered were children of the age group 3–12 years, who showed Autistic characteristic as well as typical development. The study protocol was based on the manual "Helsinki Ethical Principles and ICMR Ethical Guidelines". The data was acquired from the subjects using a 16-channel electrode, which was positioned according to the 10–20 electrode system as depicted in Fig. 4. EEG recording is done as a series of Montages (Bipolar and Referential being the two main types). Bipolar montage is chosen because of its superior ability to capture localized activity via its use of the neighbouring electrode as a reference. Signals were captured at a sampling frequency of 500 Hz from all the 16 channels.

The goal of the study is to understand the difference in activities happening in the brains of autistic kids compared to that of typically developing kids for audio and visual stimuli, and thereby find a suitable biomarker that can identify the difference at an early stage. During the experiment, the subjects were assisted to sit facing a visual screen, and the EEG electrodes were placed with the help of conductive gel and tapes. Video stimuli was used here for eight minutes. The EEG data were acquired form the subject at this time

NeuCube Model

NeuCube is a development environment to implement SNN for different problems.[40] SNN is a third-generation Artificial Neural Network model, where the neurons communicate through spikes. Networks constituted from spiking neurons are capable of processing considerably a huge amount of data in a smaller number of spikes and the communication between the neurons are estimated by the timing and existence of individual spikes.[41]

The dataset that we had acquired from the respective subjects are loaded into the NeuCube model, along with the cube containing the brain coordinates depicting the electrode from which the respective signals are acquired. This is to indicate the machine, the details about the electrodes from which the signals are captured. The mapping locations that map the features are also included. With every data loaded, the target (decides the type of dataset: Autistic brain or the typically developed brain) is also provided along. There is an inbuilt encoder module within the NeuCube architecture, which encodes the information into spike activity. Various encoders like the Ben's Spike Algorithm (BSA), Temporal Contrast (threshold-based), Step-Forward Spike Algorithm (SF) etc were available in the architecture to convert the input EEG data into spikes, of which, Threshold-based spike encoder was chosen for encoding the input EEG data points. In temporal Contrast or Threshold-based spike encoder, the spikes are

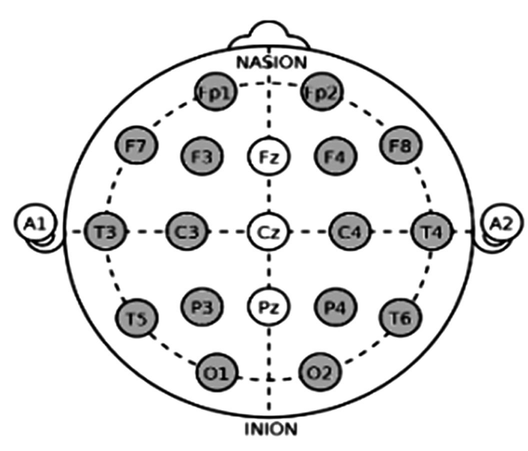

Fig. 4 — The electrode locations for an international standard 10-20 system with 16 channel montage

represented as a significant change in the intensity of the signal within a given threshold and the switching on and off events depends on the sign of changes.[42] For a given signal $S(t)$ for $t = 1,2,3, \ldots n$, a baseline $B(t)$ variation is defined during the time t with $B(1) = S(1)$. If the incoming signal intensity $S(t1)$ exceeds the baseline $B(t1-1)$ by a value Th known as the threshold, then a positive spike is encoded at t1 with the value $B(t1-1) + 1$ else, a negative spike would be encoded with a value $B(t1-1) - 1$.

Small-World Connectivity Graph

The NeuCube architecture also helps to conceptualize the variety of results obtained at each stage of the process i.e. from encoding the data to obtaining the small-world network. The first step in training is supplying the data and encoding them into spikes. The dataset from 9 samples were given to the architecture as input with differentiated target variables for the machine to identify the kind of dataset. Threshold-based encoding algorithm was used for spike encoding, with a threshold of 0.5. The threshold value was set after some trial-and-error experiments on the dataset. Once the spikes are encoded, they can be plotted and viewed as a function of time of data being fed. After training the network, the connectivity strength of the trained model, i.e. the Small World Network is obtained. The spiking activity after training the small world network using different threshold values for spike encoding is obtained.

These connections are generated homogeneously over the whole model, in a small-world manner. In the cube generated, the blue lines characterize the positive connectivity, the red lines represent the negative connectivity. Also, the brown spots indicate strong connectivity between the points. The clustering is performed based on the synaptic weights between each neuronal pairs after training. The connections can be visualized graphically as presented in Fig. 5. The thickness of lines represents the strength of the connection between the nodes, i.e. thicker the lines, greater the connection.

Matrix Generation and Coherence Analysis

To construct the matrix from the undirected graph we assigned weights to the graph, depending on the connectivity strength depicted on it, i.e. largest thickness association is represented as 1 and the least thick association is marked 0. This is done for all the trained dataset. From all the obtained matrices, the average was computed, which was used for the comparative analysis.[39] gives evidence that EEG coherence can describe the relationship between two surface electrodes, as an average of the time data points. This is done for both Autistic and typically developing samples of data. The synchronization event is now compared for coherence measurement. As a matter of limiting the number of associations to a small set, only those values were considered that showed significant differences.

According to Saunders *et al.* & Collura *et al.* the coherence analysis for EEG data can be done on 8 positions with 4 active channels, with 6 major interconnections. Each of the interconnection represents a particular brain function. The hyper-coherence and hypo-coherence estimation gave different behavioural characteristics which help in achieving the primary objective of the study. The channels that were selected for estimating the coherence levels and hence identifying their characteristics are represented in Table 1 from the study of Saunders *et al.* For example, in the Frontal-midline and Temporal Lobes T3 and T4 are two positions measured above the ear. The primary information from the electrodes in these regions generally include those involving the sensorimotor integration, logical and emotional memory formation, and storage. A hyper-coercivity in the interaction of these electrodes indicate a lack of flexibility of logical/emotional memory whereas hypo-coercivity indicates logical/emotional memory of lesser efficiency.[35]

Results and Discussion

According to the study conducted in this work, it was understood that EEG can be used as a potential biomarker in identifying and understanding the underlying behaviour of the human brain. It also helped us to identify as well as differentiate the typically developing brains with that of an Autistic brain. Since autism falls under the category of complex dis-functional disability, identification of the disorders at a very early stage could be much helpful for the patients and help them get through the disability with proper treatment and guidance. Since early detection of Autism remains under the research, it has opened the way for many novel ideas that could be taken into consideration for the study, by delving deep into the functional characteristics of it. The brain reactions, do not just depend on the stimulus, but also varies from person to person. To generalize the behaviour of a particular group of people, studies of various types were performed on the samples to conclude. The statistical analysis of the EEG signals acquired for AD and TD children are highlighted in Table 2 and 3 for few subjects.

The major motive behind the study is to detect Autism at an early stage in children and help identify the regions or nodes of the brain that actively participates for an audio and visual stimulus. Though the functional characteristics of the brain have been studied in various works, it could be seen that most of the works focus primarily on Alzheimer's disease, ADHD or Schizophrenia. Autism is an ongoing and complex field of research in the present scenario. The increasing number of Autism patients worldwide have urged to develop a means to help identify the disability long before the symptoms get evident. The human brain is a complex structure with dynamically functioning networks of neurons, that transfer messages at a very fast pace. The decoding of the information from neuron to neuron is however out of the scope of this work but decoding the information in each region of the brain can give the information regarding its behaviour. Functional connectivity in the brain can be analyzed using various methods, statistical, linear, non-linear methods etc. Most of the works referred for this study has also shown evidence of analyzing the functional connectedness of the brain network by extracting and analyzing the constituent EEG signals, i.e., alpha, beta, theta, gamma and delta waves. In this study, we have considered the EEG signals that were captured using a 16-channel EEG cap. The data were processed on a spike-based encoder system, to study the process of transmission of signals from one region (or Node) to another. Artificial intelligence was then applied to the encoder outputs to train a machine and learn about the connectivity pattern shown in each of the samples belonging to the different groups under study. The learning is based on Spiking Neural Network model, that generates a specific trajectory of spiking activities based on the input pattern of the signal. The connections can be dynamically visualized after the training of the input data as shown in Fig. 5.

It has been discussed in the preceding sections that the functional connectivity of the brain exhibits small-world organization across different time frames, and the neurons in functionally active regions of the brain are more densely interconnected and the degree of closeness indicated the strength of connectivity between them. The Fig. 6 depicts the connectivity of the brain after training the input EEG signals in the NeuCube. As in the Fig., the spiking activities can be visualized in a 3-D space where the brain coordinates are mapped. This can as well be depicted in a 2-D space. But, in both cases, a conclusion cannot be drawn as the strength of connectivity cannot be precisely drawn upon from these Figures. From Fig. 6 and Fig. 7 the connectivity graphs for Typically developing and Autism affected subject's brains can be visualized. Thicker lines indicate greater strength in connectivity between the two electrodes. As evident from the graph, there is lesser clustered connectivity observed in autistic brains as weighed against the typically developing brain.

The matrix contains the mean value of strengths for Normal and Autism samples that were encoded by the

Table 1 — Electrode pairs selected for the analysis of coherence[35]

Electrode Pair	Area	Hemisphere
F3-O1	Frontal-occipital	Intra-hemispheric
F4-O2	Frontal-occipital	
Fp1-F3	Frontal polar-frontal	
Fp2-F4	Frontal polar-frontal	
C3-P3	Central-Parietal	
C4-P4	Central-Parietal	
Fp1-Fp2	Frontal polar-frontal polar	Inter-hemispheric
F7-F8	Frontal frontal	
F3-F4	Frontal frontal	
C3-C4	Central-central	
P3-P4	Parietal-parietal	
O1-O2	Occipital-occipital	

Table 2 — Statistical analysis of EEG signals for ASD children.

S. NO	ASD		
	Mean	Median	SD
1.	7.0139	0.4166	129.2685
2.	1.03063	−0.3116	65.5353
3.	−10.0492	4.0616	77.8141
4.	−0.4547	−0.1916	56.2123
5.	0.34823	−0.19	38.4431
6.	0.8184	2.08	39.2148

Table 3 — Statistical analysis of EEG signals for TD children.

S. NO	TD		
	Mean	Median	SD
1.	0.1708	−4.0766	52.5821
2.	0.9894	−2.0733	52.3569
3.	0.0484	0.4988	22.6372
4.	0.4317	1.19	19.9154
5.	0.4447	−0.445	20.2641
6.	0.1087	0.3500	15.4075

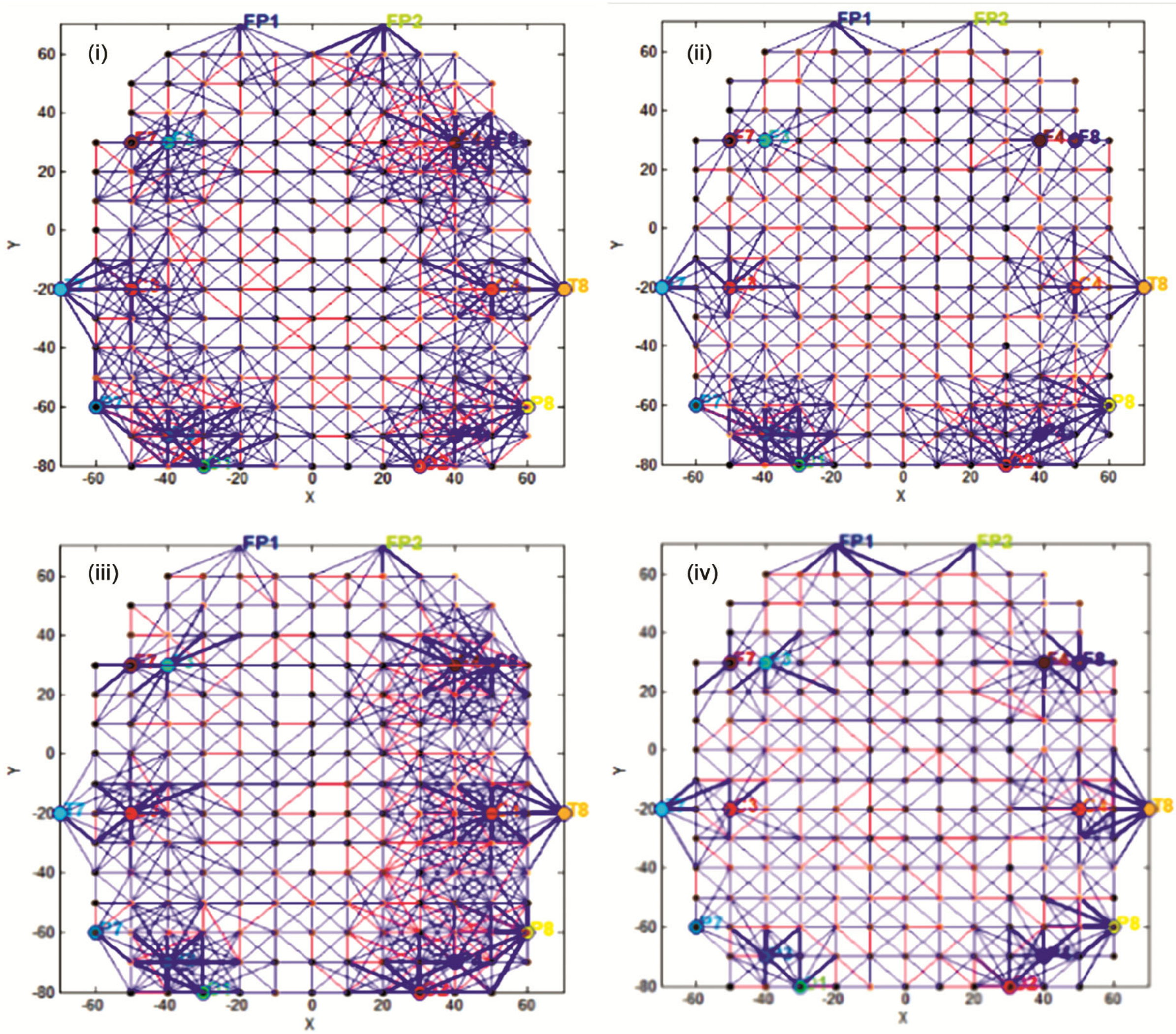

Fig. 5 — The dynamic visualization of region-wise connectivity for the (i) & (ii) Typically Developing and (iii) & (iv) Autism. The data were encoded using a Threshold of 0.06 using Threshold-based spike encoding method

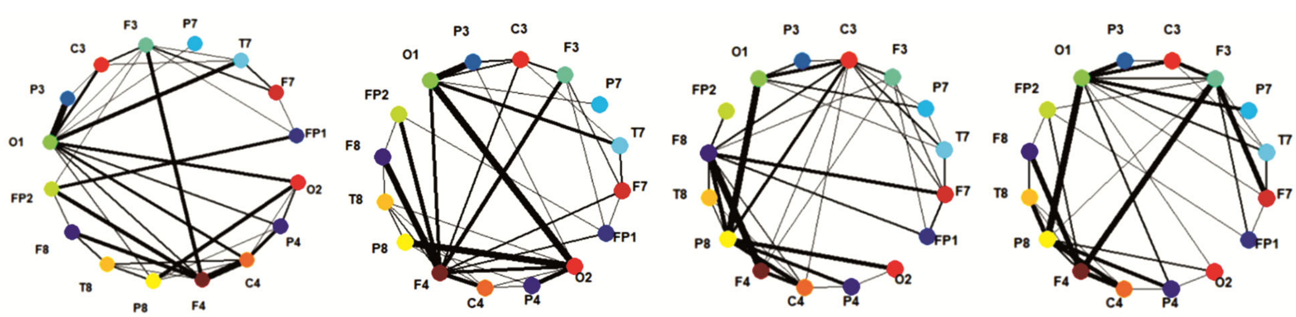

Fig. 6 — The graphical representation of connectivity in a typically developing brain data sample for audio and visual stimuli

NeuCube architecture. From the tabulated matrix, all possible combinations of electrodes with their strengths were extracted and were compared using coherence analysis. This would give us 16 × 16 combinations and 2 sets of values for comparison as shown below.

Coherence is a parameter that evaluates the synchrony between two measured signals, equivalent to a cross-correlation function. To identify the parameter that could effectively distinguish the two categories of samples, only some of the combinations

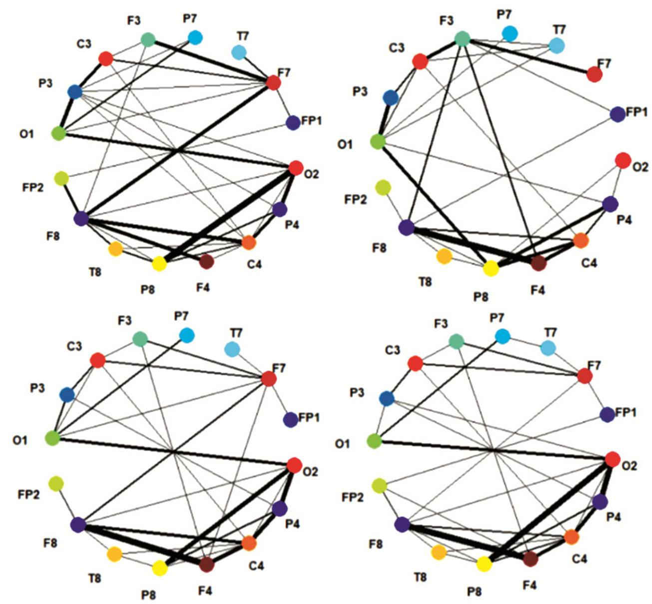

Fig. 7 — The graphical representation of connectivity in an Autism affected brain data sample for audio and visual stimuli

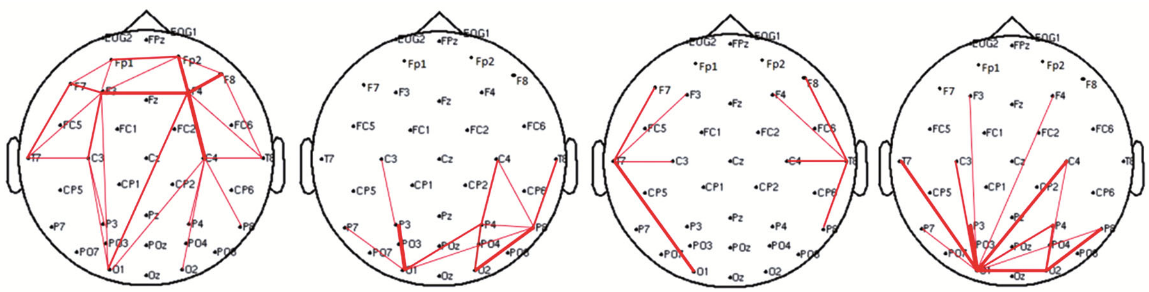

Fig. 8 — Coherence plots for TD with respect to Frontal, Parietal, Temporal and Occipital lobes of the brain

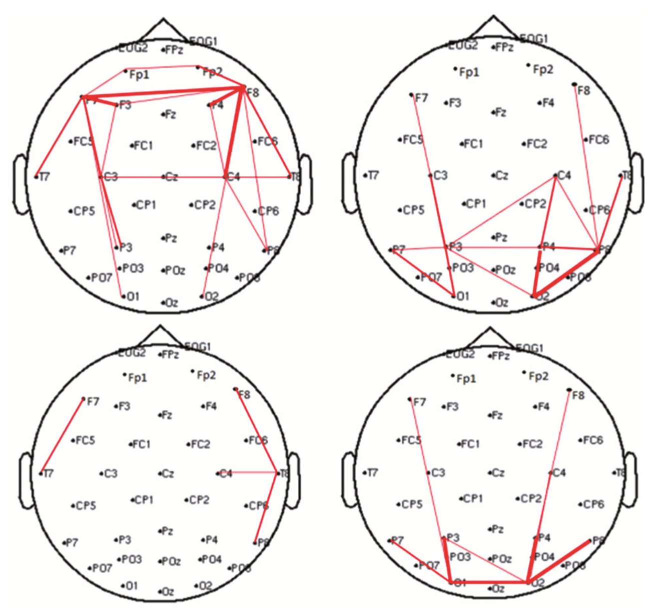

Fig. 9 — Coherence plots for AD with respect to Frontal, Parietal, Temporal and Occipital lobes of the brain

of the 16 × 16 must be taken into consideration. In Collura *et al.*[35] the functional connectivity was studied using coherence measures along with the corresponding behavioral patterns which showed changes in coherence parameter. We have tried to map our data and understand the pattern shown in the behavior of a typically developing child with that of a child affected with Autism. The coherence plots for autistic and typically developing kids are presented in Fig. 8 and Fig. 9.

Conclusions

From the comparative studies conducted in this work, we could observe a greater coherence or hyper-coherence in the channels namely C3C4, C3F7, C4F8, F7F8, F7C3, P3P4. The indications of greater coherence parameter in these channels include lack of flexibility of sensori motor integration from right to left, in terms of verbal, emotional expressions and logical memory. The results obtained from the study could indicate that the

Autism affected brains have less efficient attention towards the stimulus and shows weaker responses to them. It was also understood that the logical memory in these subjects was weak compared to a typically developing subject of the same age group. This research can be further extended by including a wide range of subjects from different geographic regions.

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